

Mixtape Application:  
**Last.fm Data Characterization**

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# Chapter 1

## Introduction

There is a never-ending debate about music and what happened to it after the dawn of the streaming age. A few very quick revolutions happened between the first appearance of MP3 files and illegal downloads and the current scenario, where most artists have their full catalog on at least one free streaming service, and many questions regarding the consequences of that process are left without answers.

Back in the day, the only ways for people to listen to music were to turn on the radio or, when choice was important, to buy large vinyl records that would eventually be stored somewhere in the house, waiting to be chosen to leave the comfort of their thick sleeves for a spin on the turntable. These records had two sides, and required an inevitable pause between the first and the second half of every record, since someone would have to go there and flip the record. This single fact, for instance, had a strong influence on how records were planned and how the sequence of songs was laid out.

Music albums were also a notable case of product tying, since they were a way for record companies to sell a large number of songs at once even though many customers only wanted a couple songs off each album. This situation started to change with the release of singles, which were cheaper, smaller vinyl records containing only a couple of songs, and, a little later, by the introduction of portable cassette tape machines, which allowed people to copy songs from different sources (radio, records or other tapes) to magnetic tapes, which were cheap, small and practical.

This was the birth of the personal playlist. Tapes were the first time people could piece together whatever tracks they wanted to listen to in whatever order they wanted and then effectively listen to them, regardless of the popularity of the artists involved, their likeliness to appear on the radio or the price of their LPs. The CD came as a more practical alternative to that system, but, down deep, the album mentality was the same.

Of course, these are baby steps when compared to the flexibility and speed of the current music industry. Many people don't even store music

on their own computers anymore and, in their cloud profiles, have access to music collections so large that they would probably take up the space of a modern house in terms of physical records. Entire albums can be bought, leased, shared or “stolen” in a few minutes over broadband connection, and crafting and delivering a mixed tape to a friend only takes a few clicks.

This abundance of material creates a very urgent need for services that somehow make it easier to find music that is interesting and relevant. There are many recommendation services that try to address this problem in different ways. Some systems are able make taste-based recommendations based on usage patterns, after a user has used them for long enough. Other systems are based on curated lists of newly released and trending items or artists, such as the user-made playlists on mixcloud<sup>1</sup> or the professional dj-curated streams on 22tracks<sup>2</sup>. Otherwise, the typically available navigation functions in media players and online streaming services are mostly based on filtering by attributes, like title, artist or genre, or return a list of similar items, computed using collaborative filtering techniques.

Now that we’re witnessing the consolidation of these streaming services, it is more important than ever to have a better understanding of how people listen to music. This is crucial for the success of any music-related service, especially the ones that intend to somehow recommend new music, or create sequences or playlists for different people to listen to.

One of the simplest ways to do that is to look at how people behave in the internet - more specifically, on Online Social Networks (OSNs). These websites are meant to extend the individual experience of society by bringing social activities to the internet, allowing people to discuss their favorite subjects and share their thoughts, opinions and feelings in a distributed and independent way, making them an interesting source of many different kinds of information.

Some of these networks carry information that is particularly valuable because it does not require active behavior to gather itself. This way, it reflects true habit and behavior that would otherwise have to be observed in an intrusive way. A great example of an ingenious way to collect such information is Last.Fm<sup>3</sup>:

Last.Fm is an online social network for music fans. It has a very ingenious way of operating: Users deliberately install a lightweight crawler on their personal computers to keep track of what they are listening to. That is called *scrobbling*. Once users have their musical history up on the website, they can interact with other users, make virtual “friends” (or find real ones that have profiles) and add them to their own profiles, leave messages, navigate through other users’ profiles to see what they listen to, among other things.

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<sup>1</sup>[www.mixcloud.com](http://www.mixcloud.com)

<sup>2</sup>[22tracks.com](http://22tracks.com)

<sup>3</sup>[www.last.fm](http://www.last.fm)

It even integrates with streaming services such as Spotify<sup>4</sup>, allowing users to upload their streaming histories directly to last.fm and listen to songs.

Even though the way people listen to music has changed drastically over the last few years, there is still little research characterizing these phenomena. In this work, we focus our attention on analyzing how people share their music listening habits with other people via the internet. In particular, we analyze *last.fm*: We seek to characterize last.fm user behavior using our analysis to shed light on how users interact in this Online Social Network (OSN), how their preferences and activities may affect and be affected by content popularity dynamics and, especially, how they listen to music.

We seek to answer the following key questions:

- What is the Last.fm user profile, age, gender, location?
- How is user activity distributed among content?
- How is the distribution of tags associated with songs?
- How can we use the knowledge of our data collection to improve the similarity measures we intend to derive from it?

Our analysis reveals interesting details about the operation of last.fm. In Particular, we show that users are young, and most are located in the United States. We also learn that there is a large difference between the amount of people who listen to popular songs and obscure songs, and that popularity should be taken into account to build concepts of similarity between songs, for recommendation purposes. And finally, we notice that users explore the tag functionality of the network quite heavily, and that important information can be derived from these tags and used for similarity and recommendation purposes.

The report is structured as follows. We discuss related work about music similarity and recommendation in chapter 2. In chapter 3 we present detailed information about the dataset used for this study. In chapter 4 we describe our detailed analysis of the user-related information in the dataset. In chapter 5 we present our analysis of artists and tracks. In chapter 6 we describe the analysis of tags. Finally, in chapter 7, we present our conclusions.

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<sup>4</sup>[www.spotify.com](http://www.spotify.com)

## Chapter 2

# Related Work

The most relevant aspects of recommendation systems are the premises they are based on, and how they build upon them. One of the most common premises is content similarity, and that it would be desirable to recommend content that is somehow similar to content that a given user enjoys. So, We present a small compilation of related works in the area of Media Similarity, Music Recommendation and Playlist Generation.

**Media item-to-item similarity computation:** Several research studies offer technical solutions to define similarity between a given pair of items, and they divide themselves among two schools. Some studies develop similarity measures that are based solely on content (objective approach), being that audio or video information — for instance, the spectral or rhythmic content of songs. On the other hand, other studies develop similarity measures that are based on user-generated data and tags, also known as collaborative filtering (subjective approach). In the context of music, different approaches to define item-to-item similarity have been studied extensively, such as content-based measures [14, 2, 12, 7, 1, 21], that analyze spectral or rhythmic properties of songs, and user-based measures [18, 9, 19, 8, 5, 10], that analyze user listening habits in online social networks or user-generated tags [19]. Many of these studies aim at building recommendation systems [14, 2, 21, 5, 20, 19].

**Music playlist generation:** Another related line of research to music navigation systems is *playlist generation*. Several people have addressed this problem from different perspectives. There are techniques that use statistical analysis of radio streams [13, 20, 4, 3], are based on multidimensional metric spaces [3, 8, 16, 15, 10], explore audio content [11], and user skipping behavior [17].

In particular, authors in [17] create playlists based on audio music similarity and skipping behavior, while authors in [6] use network flow analysis to generate playlists from a friendship graph of artists on MySpace. Maillet et al [13], in turn, present an approach to generating steerable playlists from tags linked to songs played in professional radio station playlists, and

Chen et al [3] model playlists as Markov chains, which are generated through the Latent Markov Embedding machine learning algorithm. The heuristics in [17] use acoustic similarity and present linear complexity to return the *next* item to the user, which is feasible to navigate in a collection of 2,500 items, as the authors did, but does not scale to larger collections, which is not only desirable but necessary for modern standards.

## Chapter 3

# Data collection

Last.fm provides a public API for collecting information about songs, artists, albums and tags that have been contributed by millions of users.

The collection of Last.fm was comprised of 2 steps: First we collected 0.28% of all songs from the Last.fm service (around 100 thousand songs) and their top fans, and then we continued collecting the top songs of these fans and their friends. We collected the top-25 most listened to songs of each user.

Our dataset was collected from November, 2014 to July, 2015, and contains 372,899 users (with their respective top-25 song lists), 2,060,173 songs, and 374,402 artists. Moreover, we also collected a total of 1,006,236 user-generated tags, associated with songs. In particular, 47% of songs have had at least one associated tag in our dataset.

From a total of 2,060,173 songs in our database, 983,010 have MusicBrainz Identifiers (MBID)<sup>1</sup>. This is an important source of reliability, since these entries are guaranteed to be unique, which eliminates duplicate problems, and refer to the correct media items, which avoids the occasional mismatch between the name of a song or artist in a user's computer and the actual correct name of the item, not to mention non-released live versions, non-official covers and so on.

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<sup>1</sup>MBID is a reliable and unambiguous form of music identification ([musicbrainz.org](http://musicbrainz.org)).



## Chapter 4

### User profile

We collected a total of 372,899 users from 237 countries. Table 4.1 shows the countries with most users we have collected.

| Country | # of users |
|---------|------------|
| US      | 54248      |
| BR      | 31230      |
| PL      | 25882      |
| RU      | 22979      |
| UK      | 22515      |
| DE      | 18314      |
| NL      | 7237       |
| CA      | 6931       |
| FI      | 6356       |
| FR      | 6139       |

Table 4.1: Top countries with most users

Many users did not declare their gender. Of those who did, 201,096 said they were male and 108,034 said they were female. Table 4.2 shows the number of average playcounts per gender. We can see that the average number of playcounts of male users is bigger than that of female users. Users that have not declared their gender have the smallest average playcount number.

The age range reported by the users ranges from 0 to 115 years. Figure 4.1

| Gender       | Average playcounts |
|--------------|--------------------|
| Female       | 82907.0770         |
| Male         | 113573.4874        |
| Not informed | 56797.2135         |

Table 4.2: Average playcount per gender

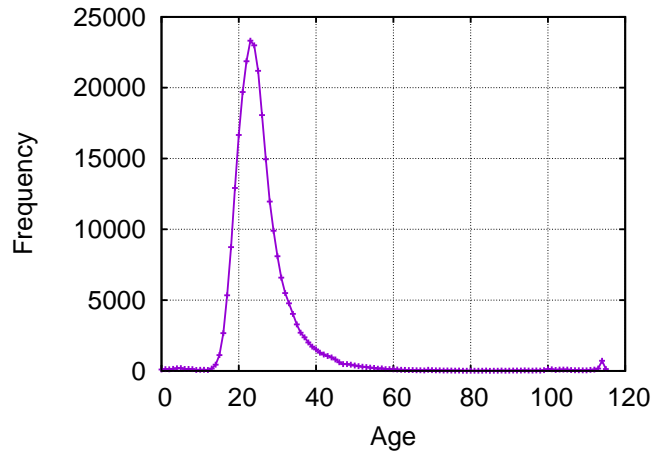


Figure 4.1: Last.fm: Users' age distribution.

shows the distribution of users' ages. We can see that the great majority of Last.fm users are from 18 to 30 years old. Over 113,000 users did not report their age.

The Figure 4.2 shows that approximately 27% of the users have listened to less than 10,000 songs, whereas 62% of the users have listened to 10,000 to 100,000 songs. In general users listen to a large amount of songs, making a vast listening history, showing that their engagement with Last.fm service lasts for a significant period of time.

Figure 4.3 shows the CDF of users' friends. Approximately 5% of the users have zero friends in Last.fm, and 50% of the users have at most 25 friends. We have only collected a maximum of 50 friends of each user, explaining the peak in the 50 number of friends point in the plot. Approximately 30% of the users have 50 friends or more.

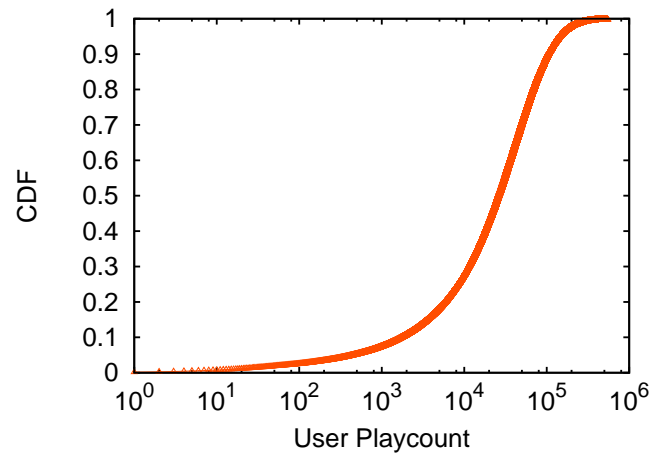


Figure 4.2: Last.fm: CDF of users' playcounts.

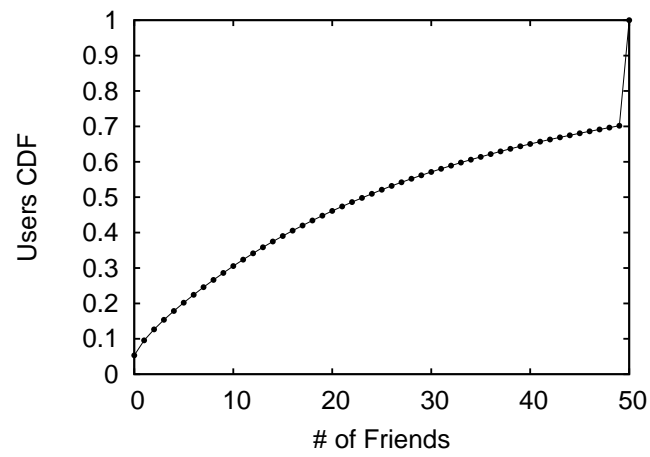


Figure 4.3: Last.fm: CDF of users' friends.

## Chapter 5

# Songs and Artists

Sometimes, Last.fm registers different items which are actually the same song, written in different ways. So, For this part of the analysis, we only took into account the songs we could match with Musicbrainz IDs, in order to avoid the risk of considering multiple issues related to track or artist name mismatch or repetition.

Figures 5.1 and 5.2 show the Cumulative Density Function (CDF) of the popularity of songs by listeners and playcount. We can observe that, in our dataset, 50% of songs were listened to by at most 1,280 unique users (0.3%); 10%, in turn, attracted attention of more than 22,685 unique users (5.9%). The most popular songs (top 1%) were listened to by more than 155,468 users (41%). The top 10 songs by number of listeners can be seen in Table 5.1, each of them with more than 1.4M listeners.

In Figure 5.2 we can see that 10% of the tracks have 1,000 playcounts or less and more than 50% have more than 10,000 playcounts.

| Track name              | Artist          | Number of listeners |
|-------------------------|-----------------|---------------------|
| Smells Like Teen Spirit | Nirvana         | 1,806,180           |
| Mr. Brightside          | The Killers     | 1,716,969           |
| Wonderwall              | Oasis           | 1,685,703           |
| Come as You Are         | Nirvana         | 1,597,611           |
| Clocks                  | Coldplay        | 1,507,981           |
| Somebody Told Me        | The Killers     | 1,490,787           |
| Take Me Out             | Franz Ferdinand | 1,462,621           |
| Karma Police            | Radiohead       | 1,431,055           |
| Viva la Vida            | Coldplay        | 1,431,034           |
| The Scientist           | Coldplay        | 1,404,877           |

Table 5.1: Top 10 songs

Figure 5.3 shows the Cumulative Density Function (CDF) of the popularity of artists by their total listeners, retrieved from Last.fm. The top 1% most popular artists ( $\approx 3,577$ ) were listened to by more than 764,000 users, while approximately 20% of the artists were listened to by only 10 users.

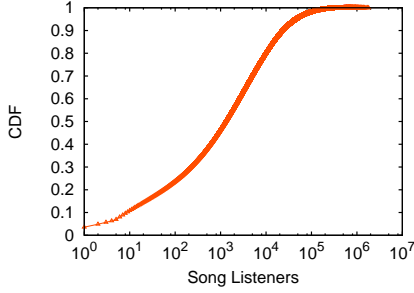


Figure 5.1: Last.fm: CDF of song popularity by listeners.

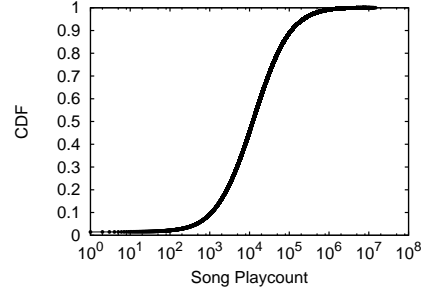


Figure 5.2: Last.fm: CDF of song popularity by playcount.

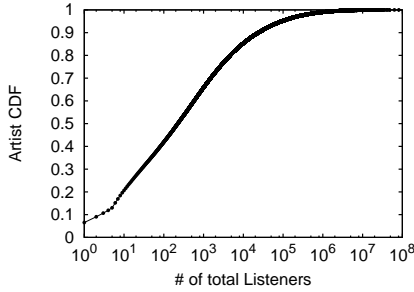


Figure 5.3: Last.fm: CDF of artist popularity by number of total listeners.

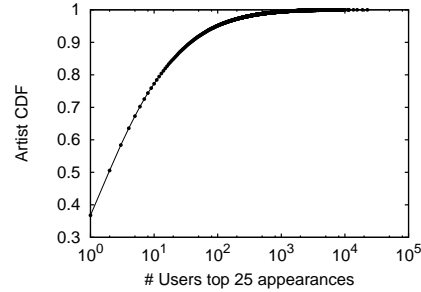


Figure 5.4: Last.fm: CDF of artist popularity by users' top 25.

Figure 5.4 shows the Artist CDF by the number of users that contain that artist in their top 25, in the users' history collected by us. More than 35% of the artists appear in only one user's top 25 songs, while 1% appear in more than 600 user's top 25 history.

Figure 5.5 shows the co-occurrence CDF between songs that co-occurred at least once. We define as a co-occurring relationship only the pair of songs that appear in at least one user's top 25 listened songs. We can see that more than 90% of the co-occurrences happen in only one user listening history, while only 1% of the relationships co-occur 10 or more times. If we consider all the  $N \times N$  pairs of all songs, most of the songs don't even co-occur in any user's top 25 songs. Therefore, initially, we can only infer the similarity between a small percentage of the songs we have collected, and have to infer similarity of the other songs from those similarities.

Figure 5.6 shows the co-occurrence CDF between artists that co-occurred at least once. We define as a co-occurring relationship only the pair of artists that appear in at least one user top 25 listened songs. We can see that 75% of the artists co-occur only in one user's top 25 songs, whereas approximately 1% of the artists co-occur in 22 users' top 25.

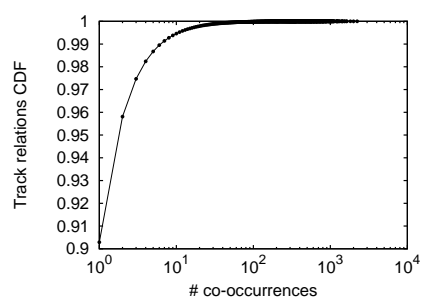


Figure 5.5: Last.fm: CDF of song co-occurrence.

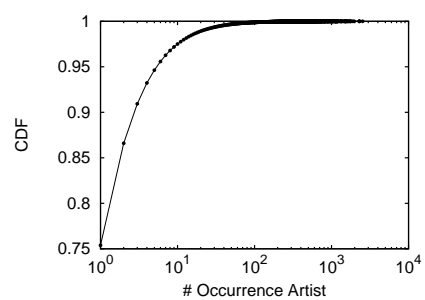


Figure 5.6: Last.fm: CDF of artist co-occurrence.

## Chapter 6

# Tags

Last.fm allows users to create and associate tags with the songs they listen to. One tag can be associated to one song from one to 100 times, allowing the users to show their agreement of a certain tag association by adding to it. We collected a total of 1,006,236 user-generated tags, associated with songs. 47% of the songs have had at least one associated tag in our dataset and considering only the songs with MusicBrainz ID, 75% of the songs were associated with at least one tag.

The top 5 most popular tags (rock, alternative, pop, indie and electronic) were associated with 541,527 songs. Table 6.1 shows the most popular tags and the number of songs associated with them.

| Tag name         | Tag count |
|------------------|-----------|
| rock             | 167,610   |
| alternative      | 101,061   |
| pop              | 96,654    |
| indie            | 88,786    |
| electronic       | 87,416    |
| alternative rock | 56,643    |
| favorites        | 56,508    |
| beautiful        | 51,870    |
| love             | 50,918    |
| awesome          | 42,364    |

Table 6.1: Top 10 tags

Figure 6.1 shows the Cumulative Density Function (CDF) of tag popularity using the number of songs associated with the tag: 62% of tags have been associated with only one song. In contrast, the top 5 most popular tags were associated with more than 87,000 songs each.

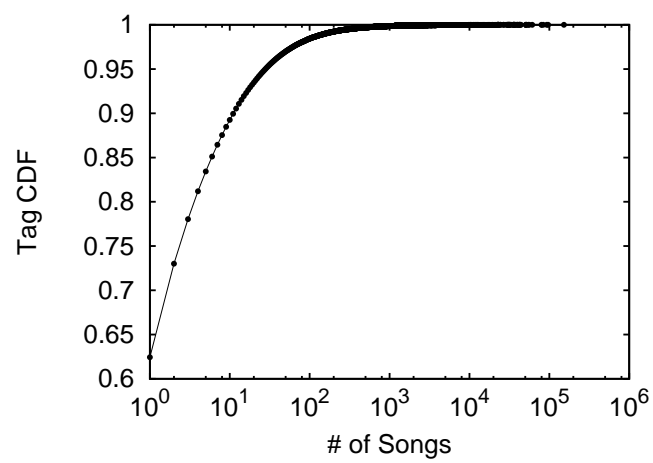


Figure 6.1: Last.fm: CDF of tag popularity.



## Chapter 7

# Conclusions

In this technical report we presented a broad characterization of Last.fm, an Online Social Network (OSN) for music fans. From that characterization we understood more about the profile of Last.fm users and how they listen to music and interact with the OSN. We also collected insights about the data we have collected, which is a small fraction of the information available in Last.fm database.

We learned that the majority of the users we have collected are young, from 18 to 30 years old, and from various countries, but the majority of users are still in the US. This will probably impact our similarity measures, which will be more accurate for the songs that appeal to this young audience and that are popular in the US, because we will have more co-occurrence data about these songs. If we want to have better similarity metrics for a specific country or region, it is fair to assume that it will be beneficial to collect more data from users from that region as a priority.

We discovered that there are songs that are listened by only a handful of users, while the top songs are listened by thousands users. This means that we will probably achieve better similarity measures for the most popular songs. Based on that information, we could develop new methods to gather more data about the less popular songs. For instance, we could collect those songs top fans histories, in order to gather more co-occurrence data from these songs. Or, in the future, we could try to ally our similarity measures based on social data to other techniques, for example, techniques that use the analysis of the content of the songs, to derive similarity measures for new or unknown songs we want to recommend.

Users also heavily used tags to classify the songs they listen to. From tags we learned that the most common genre of song in Last.fm is rock, the tag associated with the most songs in the social network. Since tags are present in most of the songs that contain a MusicBrainz ID, we can take advantage of tags to improve our similarity metrics, for instance, using tags to derive similarity of songs with zero co-occurrences to other songs. Or we

can develop navigation techniques that take advantage of tags. Finally, we can even use tags to evaluate our similarity metrics and Euclidean space, by analyzing if songs with a given tag tend to be close together or spread around the map.

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